A Global Method for the Identification of Failure Modes in Fiberglass Using Acoustic Emission

ABSTRACT: The various failure mechanisms in bidirectional glass/epoxy laminates loaded in tension are identified using acoustic emission (AE) analysis. AE data recorded during the tensile testing of a single layer specimen are used to identify matrix cracking and fiber failure, while delamination signals are characterized using a two-layer specimen with a pre-induced defect. Parametric studies using AE count rate and cumulative counts allowed damage discrimination at different levels of loading and Fuzzy C-means clustering associated with principal component analysis were used to discriminate between failure mechanisms. The two above methods led to AE waveform selection: On selected waveforms, Fast Fourier Transform (FFT) enabled calculating the frequency content of each damage mechanism. Continuous wavelet transform allowed identifying frequency range and time history for failure modes, whilst noise content associated with the different failure modes was calculated and removed by discrete wavelet transform. Short Time FFT finally highlighted the possible failure mechanism associated with each signal.

KEYWORDS: GFRP, failure modes, acoustic emission, pattern recognition, wavelet analysis

Introduction

Glass fiber reinforced polymer (GFRP) composites are widely used in aircraft, spacecraft, automotive and electronics industry. The reliability of GFRP components would considerably benefit of a robust system for monitoring in real time damage progression and discerning between different damage mechanisms, such as matrix cracking, fiber matrix splitting, delamination and fiber fracture. In-service monitoring of acoustic emission (AE), i.e., ultrasonic waves generated in materials under load, can be used for this purpose. A number of studies exist, which are aimed at finding a correlation between AE parameters and damage mechanisms [1–3]. Most studies so far have used AE signal parameters, such as rise time, counts, energy, duration, amplitude and correlated them with the occurrence of some particular damage modes [4–6]. However, the complexity of real damage patterns on composite materials suggests that the recognition of the single damage mode, being linked to the specific conditions in which it takes place inside the material, cannot be achieved using only multi-parameter analysis of AE activity [7].

For this reason, two possibilities are considered for this purpose and often combined together. Evolving to the study of signal frequency distributions and waveform pattern recognition, and starting from the artificial production of a single damage mode in composites. For example, AE parameter analysis is assisted in some cases by multi-scale method to characterize the development of failure mechanisms, such as in Siron et al. [8] on C/C composites. Unsupervised pattern recognition associated with principal component analysis (PCA) can assist in identifying the most critical damage mechanisms associated with AE signals, leading to reliable classification of AE signals into specific damage modes [9]. Godin et al. used both supervised and unsupervised classifiers to discriminate the damage mechanisms of E-glass/polyester unidirectional specimens subjected to tensile loading [10]. In this way, each AE signal can be associated to a pattern composed of multiple relevant descriptors, then the pattern can be used for classification of AE signals which are representative of the single damage mechanisms according to their similarity using multivariable data analysis based on pattern recognition algorithms. For example, unsupervised pattern recognition (UPR) is used for clustering AE events with Kohonen’s neural network [11] and k-means algorithm [12]. Huguet and Godin et al. [1,10,13] identified the typical waveform of different damage modes based on visual observation and conventional amplitude analysis of the signals. A number of UPR methods were also used by Gutkin et al. on various test configurations on CFRP laminates [14]. Signals collected from the pure resin, single fiber composites and unidirectional and cross-ply composites were classified with the Kohonen Self Organizing Map (KSOM) methods. It is widely recognized that pattern recognition technique can lead to
FIG. 2—Mechanical and AE response of single layer specimen: (a) Cumulative counts; (b) count rate.

FIG. 3—Mechanical and AE response of two-layer specimen with pre-induced delamination: (a) Cumulative counts; (b) count rate.

FIG. 4—Variation of time versus amplitude and duration of AE data: (a) For single layer specimen; (b) for two-layer specimen with pre-induced delamination.
FIG. 5—Partition index and partition coefficient for two-layer and single layer specimen.

FIG. 6—PCA visualization of the FCM clustering of tensile test: (a) For a single layer specimen; (b) for a two-layer specimen with pre-induced delamination.
good identification of AE data and a better understanding of the
damage modes [13–16]. In particular, Gang Qi studied the fracture
behavior of composite materials using wavelet based signal pro-
cessing [17]. Bussiba et al. used AE technique to track the mechan-}

cal threshold parameters for density changes in C/C composites, so
that AE parameters, such as counts, amplitude, duration, peak fre-
quency, etc., were analyzed in order to point out the possible frac-
ture sequence events [18–20]. Since AE signals in composite ma-
terials are transient, time-frequency behavior has also been studied
by Fast Fourier Transform (FFT) [21,22]. In this way, Giordano
et al. were able to identify fiber breakage using single fiber frag-
mentation tests in carbon fiber polymer composites [23]. Some im-
pulse to AE studies using FFT was given by Ni et al. [24], who
reported that, while obviously amplitude attenuates greatly with
distance between AE source and AE sensors, the frequencies of AE
signals are almost unchanged.

Time-frequency analysis has also been carried out by using
Short Time Fast Fourier Transform (STFFT) as in [25,26]. Suzuki
et al. [27] obtained scalograms for damage discrimination of longi-
tudinal GFRP composite samples subjected to tensile loading. A
major disadvantage of the Fourier analysis is that frequency infor-
mation is extracted at the expense of time information, which is
lost. In contrast, wavelet analysis transforms a signal from the time
domain into the time-frequency domain. Discrete wavelet trans-
form (DWT), which, unlike FFT but similarly to STFFT, is local-
ized both in time and frequency, is based on “mother wavelets”
which have a zero average, but are not equal to zero as a whole.
DWT provides sufficient information both for analysis and synthe-
sis of the original signal, with a significant reduction in the compu-
tation time [28]. DWT has been used on its own on AE data pro-
duced from differently delaminated glass fiber composite samples
[29]. Whenever multiple phenomena are involved and therefore
different signal clusters, UPR is also sometimes used to address
the problem of labeling the cluster [1–3,11,12,30].

In this paper, to improve classification process for composite
materials, Fuzzy C-Means clustering method (FCM) associated
with PCA is used [9]. FCM is an effective unsupervised algorithm
for automatic clustering. Parametric studies are also performed for
tracking damage initiation and accumulation at various stages of
loading, using AE count rate and cumulative counts. Acoustic
emission waveforms pertaining to the failure modes are generated
after a careful investigation of the clustered AE data and parametric
analysis. The mechanical properties and Acoustic Emission re-
sponse in GFRP composite laminates are used as a basis to identify
the AE waveforms pertaining to the single failure modes. The
dominant failure modes of the signals and their characteristic fre-
quency content are identified by performing Fast Fourier transform
on the randomly selected signals. Continuous wavelet transform
(CWT) is performed on the signal to identify the frequency range
and time history. Discrete wavelet transform (DWT) is then per-
formed to identify the noise associated with each signal. The se-
quence of failure events and their associated frequency content are
studied by performing STFFT on the signals.

Experimental Procedure

Specimen Preparation

A 300 × 300 mm GFRP composite laminate is fabricated by hand
lay-up using 12 layers of bi-directional glass mat in an epoxy ma-
trix. The laminate was cured at a pressure of 100 kg/cm² at room
temperature using a 30 ton capacity compression molding machine
for 24 h. ASTM D3039 Standard tensile specimens of size 280 × 18 × 2.78 mm³ were removed from the fabricated laminates
using water-jet cutting to avoid machining defects and maintain a
good surface finish. Single layer GFRP specimens are also fabri-
cated to discriminate failure modes such as fiber breakage and ma-
trix cracking. Finally, to introduce a delamination defect, a two-
layer GFRP specimen with pre-induced delamination is fabricated
by inserting a Teflon tape of width 10 mm in the middle portion of
the two layers.

Tensile Testing Procedure

The tensile tests are conducted on single layer, two layers with pre-
induced delamination and twelve layers specimens using an Instron
3367 (Norwood, MA, United States) universal testing machine at
room temperature. Four single layer specimens, three two-layer
specimens, and two十二-layer specimens are tested. The AE signals
are acquired using an AE system with a sampling rate of 20 Mhz
and a threshold level of 40 dB. The AE data is then analyzed using
Fast Fourier transform (FFT), Continuous wavelet transform (CWT),
and Discrete wavelet transform (DWT) for damage discrimination.

FIG. 7—Time dependency of the identified damage types during tensile tests on: (a) Single layer specimen; (b) two-layer specimen with pre-induced delamination.
specimens with induced delamination and 24 12-layer specimens have been tested. The cross-head speed was kept at 0.3 mm/min. Damage initiation and accumulation in the specimens during tensile tests is monitored by an eight channel acoustic emission monitoring system.

Acoustic Emission Monitoring

An 8 channel AE system supplied by Physical Acoustics Corporation (PAC) (Princeton, NJ, USA) with a sampling rate of 3 MHz and 40 dB pre-amplification is used for this study. Preamplifiers having a bandwidth of 10 kHz–2 MHz are used. The ambient noise was filtered using a threshold of 45 dB. AE measurements were performed using two PAC Nano 30 resonant sensors (150–400 kHz). The nominal distance between the two sensors is kept at 100 mm. High vacuum silicon grease was used as a couplant.

The amplitude distribution covers the range 0–100 dB (0 dB corresponds to 1 µv at the transducer output). After mounting the transducers, a pencil lead break procedure was used to generate repeatable AE signals for the calibration of each sensor. Velocity and attenuation studies are performed on the laminates. The average wave velocity in the material was found to be 3228 m/s. AE hardware settings are as follows: Peak definition time (PDT) = 30 µs, hit definition time (HDT) = 300 µs, hit lockout time (HLT) = 600 µs. These time intervals enable the partition of the continuous AE stress wave into separate hits, in order to analyze them using signal descriptors, such as counts, amplitude, etc. Here, suitable values for PDT, HDT and HLT have been selected, along the lines of what done already in Ref 31, dealing with CFRP, only slightly reducing PDT for the less conductive nature of glass fibers with respect to carbon fibers.

Tabs used on the laminates reduce grip noise and wave dispersion: The latter is very limited already due to the short distance between the sensors and to the low thickness of the samples used, never exceeding 3 mm. The effects of the borders is somehow reduced by considering only AE detected between the sensors and not in other areas of the samples. Of course, a consideration of attenuation effects will be required to extend this work to larger specimens such as panels or realistic structures.

Results and Discussion

The procedure adopted to associate every single AE signal with the related associated mode is schematized in Fig. 1: In the following Sections, the results obtained in the individual phases of the procedure are reported.

Multi-Parameter Analysis of AE Data

The failure modes in GFRP composite laminates are identified using various AE parameters (cumulative ring-down counts, count rate, amplitude, and duration).

Acoustic emission technique was utilized in tracking the damage accumulation profile during loading up to failure in terms of AE count rate and cumulative counts. The damage signals were identified by the sequence of events in the failure process, from matrix micro cracking, matrix macro cracking, and delamination followed by fiber break [18]. The difference between micro- and macro-cracking is basically that the saturation, i.e., a diffuse coalescence, of the former brings to the generation of the latter, which also result in a substantial increase of AE count rate [32].

Acoustic emission starts after the initiation of local plastic deformation, and AE counts increase steeply up to failure. Dealing
with the single layer specimen, in Fig. 2(a) and 2(b) three stages until failure are visible. The first stage corresponds to damage initiation involving lower count rate. The second stage is damage accumulation in which the matrix micro cracking progresses. This is indicated by a sudden and abrupt increase in cumulative counts and count rate. The final stage corresponds to an unstable crack growth where there is a sharp increase in counts rate. In the case of the two-layer specimen with pre-induced delamination, as shown in Fig. 3(a) and 3(b), during the initial stage of loading, up to 350 s, the variation of cumulative AE counts versus time is almost flat, which indicates matrix micro-cracking [18]. Further loading results in a sudden increase in AE count rate, due to matrix micro-cracking progressing at a faster rate. The final sharp increase in the count rate is deemed representing fiber-matrix debonding and fiber failure.

Damage discrimination of GFRP laminates based on multiscale approach involves the variation of amplitude and duration of the AE events with time. Several domains were defined and correlated with the physical damage of the specimens subjected to tensile loading with AE monitoring.

Figure 4(a) and 4(b) show representation of time, amplitude and duration of the AE data recorded during tensile test of GFRP single layer composite laminates and of a specimen with pre-induced delamination, respectively. For single layer specimens, AE data are distributed in three intervals of amplitudes: Low (48–65 dB), medium (65–85 dB) and high (85–99 dB) amplitude ranges. From this amplitude classification of the AE signals, a correlation with the duration of the AE data was made. Only few events were recorded during the first linear parts of the loading history curve (<140 s), which in their totality corresponded to low amplitude and low duration (<400 µs) events. The first linear domain was attributed to the limited matrix micro cracking [8]. In the time interval between 140 and 607 s, where this latter corresponds to the moment when the maximum load is reached, the acoustic activity increased and medium amplitude signals associated with low duration events were also recorded. The second stage is almost linear and was ended by a significant increase in cumulative counts, which indicates damage intensification leading to the increase of the matrix micro cracking within the ply. On the double layer specimen with pre-induced delamination, AE signals with low/medium amplitude and medium duration signals occur at the initial stages of loading. These are likely to indicate that the pre-induced delamination is active and still no further damage is present. In this way, delamination can be associated with low/medium amplitude and medium/high duration events. In contrast, high amplitude and low duration events which follow may be attributed to fiber failure [8].

FIG. 9—Typical AE signal for two-layers specimen with pre-induced delamination: (a) Matrix micro cracking (A-signal); (b) delamination (B-signal); (c) fiber breakage (C-signals); and (d) Matrix macro cracking (D-signal).
Clustering of Data from Multi-Parameter Analysis of AE Data

Fuzzy C-Means (FCM) clustering accompanied by PCA is used for clustering AE data obtained during tensile testing [9]. A number of dominant AE parameters, such as rise time, counts, energy, duration and amplitude are used for clustering. For single layer specimen the optimal number of clusters obtained by cluster validity tests is found to be two, whilst it was found to be three for specimens with pre-induced delamination. This has been established by the measurement of the partition index and the partition coefficient. Partition index measures compactness of the clusters and average inter-cluster distance, while partition coefficient measures the degree of overlapping between the clusters [33]. For single layer specimen the partition index and the partition coefficient correspond to 0.34 and 0.97, while for the two-layer specimen with pre-induced delamination these correspond to 0.69 and 0.95, respectively, as reported in Fig. 5. It is suggested that some degree of overlapping exists between waves from failure process and reflections from specimen borders, as it is often the case for AE detection during testing of small specimens.

PCA is carried out in order to visualize the results in a two-dimensional subspace. The representation shows that most of the patterns are concentrated into three groups, defined as Class-A, Class-B, Class-C signals, which are representative of the failure mechanisms such as matrix cracking, delamination and fiber break [34]. Figure 6, 7(a), and 7(b) show the plot of number of hits versus time for single layer and two-layer specimens with pre-induced delamination respectively, after performing PCA. In both single layer and two-layer specimens, most AE activity classified as being Class A signals is detected at the initial stage of loading which corresponds to matrix cracking. AE activity corresponding to fiber failure is found to be predominant just prior to failure. It was also observed that matrix cracking and delamination modes were occurring during the entire course of the test. Hence the discrimination of damage using unsupervised pattern recognition (UPR) involves some degree of overlapping.

Identification of AE Waveforms

Typical AE waveforms pertaining to hit data and possibly related to the failure modes during tensile test monitoring are identified from cluster analysis and parametric analysis. Waveforms for single layer specimen and two layers with pre-induced delamination specimen are shown in Figs. 7 and 8, respectively.

Frequency domain of AE signals using FFT is performed to suppress undesired interferences. FFT allows pointing out the predominant frequency which is directly related to the damage mechanism of the specimens subjected to tensile test.

Each occurrence of damage generates an AE signal which is related to the amount of strain energy released. Therefore each AE waveform has a feature, in the sense that its amplitude, duration and frequency content are related in some way to the damage mechanism [35]. (a) Fiber breakage generates medium to high amplitude and short duration events with high frequency content. (b) Matrix cracking has low to medium amplitude, short to moderate duration with medium frequency content. (c) Fiber debonding as well as delamination generates AE hits which covers the whole range of amplitudes and typically have long duration and low frequency content [9].

Figure 9 and 10 show the characteristic frequencies \( f_c \) obtained using FFT for different failure mechanisms, namely delamination, matrix micro cracking, matrix macro cracking, and fiber failure. After a thorough investigation of the AE waveforms it is found that there are four different ranges of characteristic frequencies involved. The frequency range of 92–153 kHz corresponds to delamination. The frequency range of 238–285 kHz corresponds to matrix cracking. Fiber breakage corresponds to a frequency range of 299–
352 kHz. The proximity of extreme values of the two latter intervals suggest that in some cases overlapping is possible. However, for these materials with this set-up and sensor selection this was not revealed. This suggests that the four modes of failure in fiberglass can be distinguished in the present test conditions, based on frequency, which gives scope to the waveform analysis that follows (Fig. 11).

**Time-Frequency Analysis of AE Signals Using Wavelet Transform (WT)**

As AE signals are not stationary, to enhance the relevance of their descriptors, wavelet analysis has also been performed. The Wavelet Transform (WT) can decompose the AE signals in time and wavelet scale domains and highlight the differences in these waves. It makes possible to distinguish between the different damage modes from frequency ranges where highest signal energy is detected. Two typical AE signals which correspond to the failure modes such as delamination and fiber failure are included for wavelet analysis.

CWT is performed as it is superior to all other transformations in providing an exact time-frequency plot of the AE signals [36]. CWT is applied to B-signal (delamination) and C- signal (fiber breakage): These are shown in Fig. 12(a) and 12(b) respectively. Daubechies wavelets are then employed to make use of the time and frequency domain information of the signals for classifying them. In Figs. 13 and 14 the results of the wavelet transform analysis are reported for the B-signal and C-signal, respectively. In particular, (a) their identification by frequency range using CWT, (b) their five levels of decomposition using Daubechies wavelets, (c) the subsequent highlighting of their most important frequency content, and finally (d) their reconstruction as de-noised signals are all represented. These will be explained in more detail below.

(a) The time-frequency representation obtained shows the high energy areas which are used to identify the failure mechanisms. It is also found that the frequency content is prolonged and stretched more for the Class C-signals than for Class B-signals. Class C-signals which are representative of fiber failure are mainly in the frequency range of 250–350 kHz, while Class B-signals corresponding to delamination are in the frequency range of 90–180 kHz. Class B-signal therefore exhibit a lower frequency than Class C-signals. The time-frequency representation highlights qualitative differences between the two signatures from delamination and fiber failure.
Further DWT is used to decompose the analyzed AE signal. In DWT, a signal may be represented by its approximations and details. An approximation is the high-scale, low frequency component of the signal. The details are the low-scale, high frequency components. The summation of the signals obtained at each level reconstructs the primary or original AE signal. Daubechies wavelets with four vanishing moments are used for the purpose of decomposition. The Daubechies wavelets have a high regularity that is defined by their order of differentiability as compared with the Meyer wavelet and the Morlet wavelet that are localized harmonic functions. The regularity of Daubechies wavelet is useful in estimations of the local properties of signals, such as breakdown points, and discontinuities in higher derivatives. Because AE signals due to damage generally have these transient features, Daubechies wavelets have been used to analyze them.

By applying Fast Fourier transform on each detailed coefficient, the frequency band associated to each level of decomposition is highlighted. It can be observed that for detail coefficients from D5-D1 there is an increase in frequency band width up to 1500 kHz. With this decomposition the most important frequency content is highlighted. The frequency content for Class B-signals (delamination) is in the range 93–144 kHz and their details are found to be predominant in D4 and D5, whereas for Class C-signals (fiber failure) the frequency content is in the range 138–440 kHz and their details are found to be predominant in D3 and D4. These frequency bands are characteristic of the different damage mechanisms, such as delamination and fiber failure. With the available details and their frequency ranges, the level of noise can also be identified in each signal associated with the failure mode.

Due to the presence of noise in AE signals, it becomes difficult to give a right interpretation to the AE signature. To analyze the AE signals, it is essential to eliminate or reduce noise in them. Noise can be reduced using filters, or by decreasing the gain and/or increasing the threshold. As AE data involve both low frequency and high frequency noise, to avoid loss of information in the signal, a soft threshold is preferred. Some traces of the noise may remain nearby the singularities if a hard threshold is selected. The removal action takes place where the signal is regular. The soft thresholding estimation reduces the noise effect in the discontinuities at the price of reducing the amplitude of the coefficients. Though various signal processing tools like Fast Fourier Transform and Windowed Fourier Transform are available to analyze these signals, it is found that the Discrete Wavelet Transform (DWT) is a more appropriate technique which can be used to de-noise the transient AE signals [17].

The test signals pertaining to the failure modes are always accumulated with random noise at all instant of times during loading. AE transient signals associated with mechanical noise, due to the testing system, to more general background noise, to the rapid increase in crack growth and opening, and to noise emerging on the specimen at the time of failure are all acquired. The recovery of AE signals from noisy data, acquired during tensile test, was carried out using wavelet transformation technique. Denoising is performed on the AE transient signals using DWT and the actual signature corresponding to the failure mode is identified.

DWT is applied on the test signals using Daubechies (four vanishing moments) and the signals are further reconstructed. The reconstructed signals are devoid of noise. The signatures of the test signals are typically low frequency signals enveloped by relatively high frequency background noise. So to de-noise these signals, the detail coefficients are heavily thresholded. To eliminate the noise and to identify the exact frequency content of the damage mechanisms this thresholding is done with the available details of the frequency bands for the different types of failure modes.

Failure Modes in AE Signals

At initial stages of loading, low and medium frequencies are dominant, which are related to delamination and matrix cracking, respectively. With further loading, high frequency signal events are detected which are related to fiber failure and propagation of microcracks. The multi-layer cracking is the first to be active, followed by matrix cracking, delamination and fiber breakage, as reported in literature [18].

Failure modes associated with AE signals for bi-directional GFRP laminates have been identified using a single layer and two-layer specimens with pre-induced delamination. The results obtained using the above specimens are correlated with those of a 12
layer specimen subjected to tension with AE monitoring. Fig. 15(a) and 15(b) represent the dominant fiber failure modes associated with other failure modes for a 12 layer specimen in time domain and frequency, respectively. STFFT is used to study the dominant failure mode and the failure modes associated with that. Figure 15(c) shows the peak frequencies of all failure modes, such as matrix micro and macro cracking, delamination and fiber failure, for a 12 layer specimen. This allows validating the results obtained for single layer and two-layer specimens with pre induced delamination with that from 12-layer specimen. In this plot, STFFT allowed selecting a single waveform containing all failure modes. From the above results is observed that the peak frequencies corresponding to the failure mechanisms of 12 layer specimen are identical with that of single layer and two-layer specimens with pre-induced delamination. The delamination mode has long duration with low frequency, matrix cracking mode has short to moderate duration with medium frequency and dominant fiber failure mode has short duration with high frequency.

Scanning Electron Microscope (SEM) was performed on the failure surfaces to characterize and classify the main failure mechanisms with focus on damage like matrix micro cracking, matrix macro cracking, delamination and fiber failure, as shown in Fig. 16(a)–16(d). Most of the damage is located in the failure envelope, including large intra and inter-layer delamination as well as fiber failure. The damage and failure process appear to be mainly due to local shear components, which ease fiber pull-out, resulting finally in mode I fiber fracture. Based on the microscopy analysis of damage, an approach using AE waveform parameter as damage indicators was identified. The parametric analysis, used as multi-scale approach, provides evidence of a correlation between the initiation and the propagation of micro cracks for low duration and low amplitude events. The intra and inter-layer cracks initiation and propagation responsible for the delamination were associated to medium duration and high amplitude events were assigned to fiber breakage. Finally high duration and high amplitude events were associated to the macro crack initiation and propagation.

Conclusions

The purpose of this study was developing an automated procedure of the signals in order to identify the damage mechanism sources of AE during monotonic mechanical tests on glass fiber composites.
The interest of this investigation relies more on the optimization of the procedure than on the specific numerical results obtained, which are material- and sensor-depandant, since such procedure will permit the continuous monitoring of the integrity of the composite structure. It was applied to AE signals detected by surface-mounted piezoelectric transducers. An unsupervised classifier, mechanical behavior with AE response and multi-scale approach were used to identify the failure mechanisms during tensile loading with AE monitoring of GFRP laminates. The signal processing procedure permitted successfully to identify the damage mechanisms. The labeling of AE signals with specific damage modes was carried out by waveform comparison and FFT analysis. STFFT analysis was carried out to analyze the different failure events and associate them with their dominant frequency mode. Time information with frequency range for specific failure modes like matrix microcracking, delamination, fiber breakage and matrix macro-cracking are obtained.

In general, comparing mechanical properties and acoustic emission response in GFRP composites laminates using pattern recognition method and multiscale approach demonstrated a successful approach to identifying AE waveform with the aim of discriminating the failure mechanism. The dominant failures in each signal are identified by using FFT (finding frequency contents in the signals). The sequence of failure events in AE waveform are performed using STFFT. Time information with frequency range of failure modes are studied using wavelet transformation technique. The whole procedure shows potential in the investigation of failure mechanisms in composite materials.
References


